In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [ ]:
```
df = pd.read_csv('data/diabetes.csv')
df.head(20)
```

Out[ ]:

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Outcome |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 6 | 148 | 72 | 35 | 0 | 33.6 | 0.627 | 50 | 1 |
| **1** | 1 | 85 | 66 | 29 | 0 | 26.6 | 0.351 | 31 | 0 |
| **2** | 8 | 183 | 64 | 0 | 0 | 23.3 | 0.672 | 32 | 1 |
| **3** | 1 | 89 | 66 | 23 | 94 | 28.1 | 0.167 | 21 | 0 |
| **4** | 0 | 137 | 40 | 35 | 168 | 43.1 | 2.288 | 33 | 1 |
| **5** | 5 | 116 | 74 | 0 | 0 | 25.6 | 0.201 | 30 | 0 |
| **6** | 3 | 78 | 50 | 32 | 88 | 31.0 | 0.248 | 26 | 1 |
| **7** | 10 | 115 | 0 | 0 | 0 | 35.3 | 0.134 | 29 | 0 |
| **8** | 2 | 197 | 70 | 45 | 543 | 30.5 | 0.158 | 53 | 1 |
| **9** | 8 | 125 | 96 | 0 | 0 | 0.0 | 0.232 | 54 | 1 |
| **10** | 4 | 110 | 92 | 0 | 0 | 37.6 | 0.191 | 30 | 0 |
| **11** | 10 | 168 | 74 | 0 | 0 | 38.0 | 0.537 | 34 | 1 |
| **12** | 10 | 139 | 80 | 0 | 0 | 27.1 | 1.441 | 57 | 0 |
| **13** | 1 | 189 | 60 | 23 | 846 | 30.1 | 0.398 | 59 | 1 |
| **14** | 5 | 166 | 72 | 19 | 175 | 25.8 | 0.587 | 51 | 1 |
| **15** | 7 | 100 | 0 | 0 | 0 | 30.0 | 0.484 | 32 | 1 |
| **16** | 0 | 118 | 84 | 47 | 230 | 45.8 | 0.551 | 31 | 1 |
| **17** | 7 | 107 | 74 | 0 | 0 | 29.6 | 0.254 | 31 | 1 |
| **18** | 1 | 103 | 30 | 38 | 83 | 43.3 | 0.183 | 33 | 0 |
| **19** | 1 | 115 | 70 | 30 | 96 | 34.6 | 0.529 | 32 | 1 |

Replacing zeros with null

In [ ]:
```
df['Glucose'].replace(0, np.nan, inplace=True)
df['BloodPressure'].replace(0, np.nan, inplace=True)
df['SkinThickness'].replace(0, np.nan, inplace=True)
df['Insulin'].replace(0, np.nan, inplace=True)
df['BMI'].replace(0, np.nan, inplace=True)
df['DiabetesPedigreeFunction'].replace(0, np.nan, inplace=True)
df['Age'].replace(0, np.nan, inplace=True)
```

In [ ]:
```
df.duplicated().any()
```

Out[ ]:
```
False
```

In [ ]:
```
df.isna().sum()
```

Out[ ]:
```
Pregnancies                 0
Glucose                     5
BloodPressure              35
SkinThickness             227
Insulin                   374
BMI                        11
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [ ]:
```
df.describe()
```

Out[ ]:

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 768.000000 | 763.000000 | 733.000000 | 541.000000 | 394.000000 | 757.000000 | 768.000000 | 768.000000 | 76 |
| **mean** | 3.845052 | 121.686763 | 72.405184 | 29.153420 | 155.548223 | 32.457464 | 0.471876 | 33.240885 | |
| **std** | 3.369578 | 30.535641 | 12.382158 | 10.476982 | 118.775855 | 6.924988 | 0.331329 | 11.760232 | |
| **min** | 0.000000 | 44.000000 | 24.000000 | 7.000000 | 14.000000 | 18.200000 | 0.078000 | 21.000000 | |
| **25%** | 1.000000 | 99.000000 | 64.000000 | 22.000000 | 76.250000 | 27.500000 | 0.243750 | 24.000000 | |
| **50%** | 3.000000 | 117.000000 | 72.000000 | 29.000000 | 125.000000 | 32.300000 | 0.372500 | 29.000000 | |
| **75%** | 6.000000 | 141.000000 | 80.000000 | 36.000000 | 190.000000 | 36.600000 | 0.626250 | 41.000000 | |
| **max** | 17.000000 | 199.000000 | 122.000000 | 99.000000 | 846.000000 | 67.100000 | 2.420000 | 81.000000 | |

In [ ]:
```
data = df.values
X = data[:, :-1]
y = data[:, -1]
pd.DataFrame(X)
```

Out[ ]:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| **0** | 6.0 | 148.0 | 72.0 | 35.0 | NaN | 33.6 | 0.627 | 50.0 |
| **1** | 1.0 | 85.0 | 66.0 | 29.0 | NaN | 26.6 | 0.351 | 31.0 |
| **2** | 8.0 | 183.0 | 64.0 | NaN | NaN | 23.3 | 0.672 | 32.0 |
| **3** | 1.0 | 89.0 | 66.0 | 23.0 | 94.0 | 28.1 | 0.167 | 21.0 |
| **4** | 0.0 | 137.0 | 40.0 | 35.0 | 168.0 | 43.1 | 2.288 | 33.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **763** | 10.0 | 101.0 | 76.0 | 48.0 | 180.0 | 32.9 | 0.171 | 63.0 |
| **764** | 2.0 | 122.0 | 70.0 | 27.0 | NaN | 36.8 | 0.340 | 27.0 |
| **765** | 5.0 | 121.0 | 72.0 | 23.0 | 112.0 | 26.2 | 0.245 | 30.0 |
| **766** | 1.0 | 126.0 | 60.0 | NaN | NaN | 30.1 | 0.349 | 47.0 |
| **767** | 1.0 | 93.0 | 70.0 | 31.0 | NaN | 30.4 | 0.315 | 23.0 |

768 rows × 8 columns

In [ ]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
```

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state=1)
```

In [ ]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(614, 8)
(154, 8)
```

labels = Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction, Age

Mean - Glucose, BloodPressure, SkinThickness, BMI (columns:1,2,3,5)

Median - Insulin, DiabetesPedigreeFunction, Age (columns:4,6,7)

In [ ]:
```
mean_imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
median_imputer = SimpleImputer(missing_values=np.nan, strategy='median')
min_max_scaler = MinMaxScaler(feature_range=(0,1))
```

In [ ]:
```
X_train[:, (1,2,3,5)] = mean_imputer.fit_transform(X_train[:, (1,2,3,5)])
X_train[:, (4,6,7)] = median_imputer.fit_transform(X_train[:, (4,6,7)])
X_test[:, (1,2,3,5)] = mean_imputer.transform(X_test[:, (1,2,3,5)])
X_test[:, (4,6,7)] = median_imputer.transform(X_test[:, (4,6,7)])
```

In [ ]:
```
pd.DataFrame(X_train).isna().any()
```

Out[ ]:
```
0    False
1    False
2    False
3    False
4    False
5    False
6    False
7    False
dtype: bool
```

In [ ]:
```
pd.DataFrame(X_train)
```

Out[ ]:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| **0** | 9.0 | 145.0 | 80.0 | 46.000000 | 130.0 | 37.9 | 0.637 | 40.0 |
| **1** | 10.0 | 129.0 | 62.0 | 36.000000 | 125.0 | 41.2 | 0.441 | 38.0 |
| **2** | 7.0 | 102.0 | 74.0 | 40.000000 | 105.0 | 37.2 | 0.204 | 45.0 |
| **3** | 8.0 | 120.0 | 78.0 | 28.770686 | 125.0 | 25.0 | 0.409 | 64.0 |
| **4** | 2.0 | 120.0 | 76.0 | 37.000000 | 105.0 | 39.7 | 0.215 | 29.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **609** | 2.0 | 157.0 | 74.0 | 35.000000 | 440.0 | 39.4 | 0.134 | 30.0 |
| **610** | 7.0 | 187.0 | 50.0 | 33.000000 | 392.0 | 33.9 | 0.826 | 34.0 |
| **611** | 13.0 | 126.0 | 90.0 | 28.770686 | 125.0 | 43.4 | 0.583 | 42.0 |
| **612** | 4.0 | 171.0 | 72.0 | 28.770686 | 125.0 | 43.6 | 0.479 | 26.0 |
| **613** | 9.0 | 102.0 | 76.0 | 37.000000 | 125.0 | 32.9 | 0.665 | 46.0 |

614 rows × 8 columns

Applying min-max scaling on all columns

In [ ]:
```
X_train = min_max_scaler.fit_transform(X_train)
X_test = min_max_scaler.transform(X_test)
```

In [ ]:
```
pd.DataFrame(X_train)
```

Out[ ]:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| **0** | 0.600000 | 0.655844 | 0.571429 | 0.423913 | 0.138387 | 0.402863 | 0.246325 | 0.372549 |
| **1** | 0.666667 | 0.551948 | 0.387755 | 0.315217 | 0.132371 | 0.470348 | 0.159020 | 0.333333 |
| **2** | 0.466667 | 0.376623 | 0.510204 | 0.358696 | 0.108303 | 0.388548 | 0.053452 | 0.470588 |
| **3** | 0.533333 | 0.493506 | 0.551020 | 0.236638 | 0.132371 | 0.139059 | 0.144766 | 0.843137 |
| **4** | 0.133333 | 0.493506 | 0.530612 | 0.326087 | 0.108303 | 0.439673 | 0.058352 | 0.156863 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **609** | 0.133333 | 0.733766 | 0.510204 | 0.304348 | 0.511432 | 0.433538 | 0.022272 | 0.176471 |
| **610** | 0.466667 | 0.928571 | 0.265306 | 0.282609 | 0.453670 | 0.321063 | 0.330512 | 0.254902 |
| **611** | 0.866667 | 0.532468 | 0.673469 | 0.236638 | 0.132371 | 0.515337 | 0.222272 | 0.411765 |
| **612** | 0.266667 | 0.824675 | 0.489796 | 0.236638 | 0.132371 | 0.519427 | 0.175947 | 0.098039 |
| **613** | 0.600000 | 0.376623 | 0.530612 | 0.326087 | 0.132371 | 0.300613 | 0.258797 | 0.490196 |

614 rows × 8 columns

In [ ]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report, cor
```

## Naive Bayes Classification

In [ ]:
```
gnb = GaussianNB()
gnb.fit(X_train, y_train)
```

Out[ ]:
```
GaussianNB()
```

In [ ]:
```
y_pred_gnb = gnb.predict(X_test)
```

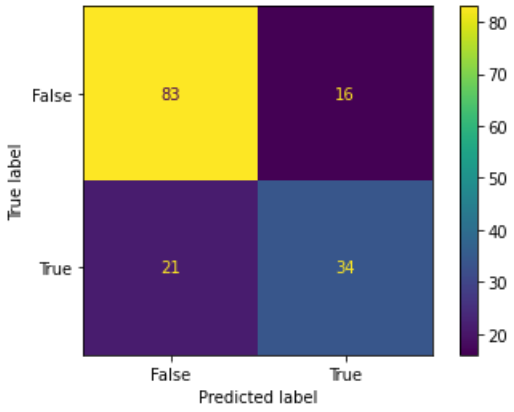
In [ ]:
```
accuracy_gnb = accuracy_score(y_test, y_pred_gnb)
precision_gnb = precision_score(y_test, y_pred_gnb)
recall_gnb = recall_score(y_test, y_pred_gnb)
f1_gnb = f1_score(y_test, y_pred_gnb)
```

In [ ]:
```
cr_gnb = classification_report(y_test, y_pred_gnb, output_dict=True, zero_division='warn')
pd.DataFrame(cr_gnb)
```

Out[ ]:

| | 0.0 | 1.0 | accuracy | macro avg | weighted avg |
|---|---|---|---|---|---|
| **precision** | 0.798077 | 0.680000 | 0.75974 | 0.739038 | 0.755907 |
| **recall** | 0.838384 | 0.618182 | 0.75974 | 0.728283 | 0.759740 |
| **f1-score** | 0.817734 | 0.647619 | 0.75974 | 0.732677 | 0.756979 |
| **support** | 99.000000 | 55.000000 | 0.75974 | 154.000000 | 154.000000 |

In [ ]:
```
cm_display_gnb = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pred_gnb), display_labels=
cm_display_gnb.plot()
plt.show()
```




# KNN Classification

Selecting best value for n_neighbors using GridsearchCV

In [ ]:
```
knn_test = KNeighborsClassifier()
#create a dictionary of all values we want to test for n_neighbors
param_grid = {'n_neighbors': np.arange(1, 40)}
#use gridsearch to test all values for n_neighbors
knn_gscv = GridSearchCV(knn_test, param_grid, cv=5)
knn_gscv.fit(X_train, y_train)
```

Out[ ]:
```
GridSearchCV
estimator: KNeighborsClassifier
KNeighborsClassifier
```

In [ ]:
```
knn_gscv.best_params_
```

Out[ ]:
```
{'n_neighbors': 27}
```

Hence, 27 gives best result for n_neighbors

In [ ]:
```
knn = KNeighborsClassifier(n_neighbors=27)
knn.fit(X_train, y_train)
```

Out[ ]:
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=27)
```

In [ ]:
```
y_pred_knn = knn.predict(X_test)
```

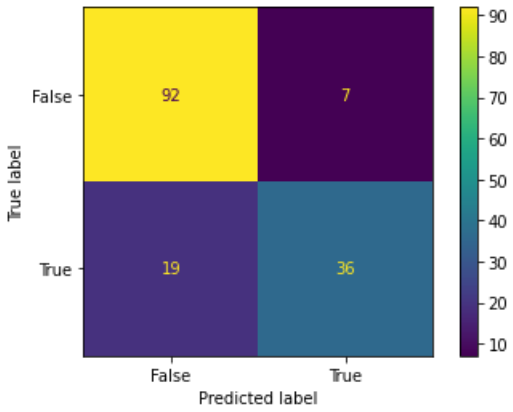
In [ ]:
```
accuracy_knn = accuracy_score(y_test, y_pred_knn)
precision_knn = precision_score(y_test, y_pred_knn)
recall_knn = recall_score(y_test, y_pred_knn)
f1_knn = f1_score(y_test, y_pred_knn)
```

In [ ]:
```
cr_knn = classification_report(y_test, y_pred_knn, output_dict=True, zero_division='warn')
pd.DataFrame(cr_knn)
```

Out[ ]:

| | 0.0 | 1.0 | accuracy | macro avg | weighted avg |
|---|---|---|---|---|---|
| **precision** | 0.828829 | 0.837209 | 0.831169 | 0.833019 | 0.831822 |
| **recall** | 0.929293 | 0.654545 | 0.831169 | 0.791919 | 0.831169 |
| **f1-score** | 0.876190 | 0.734694 | 0.831169 | 0.805442 | 0.825656 |
| **support** | 99.000000 | 55.000000 | 0.831169 | 154.000000 | 154.000000 |

In [ ]:
```
cm_display_knn = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pred_knn), display_labels=
cm_display_knn.plot()
plt.show()
```




## SVM Classification

In [ ]:
```
svm = SVC()
svm.fit(X_train, y_train)
```

Out[ ]:
```
▾ SVC
SVC()
```

In [ ]:
```
y_pred_svm = svm.predict(X_test)
```

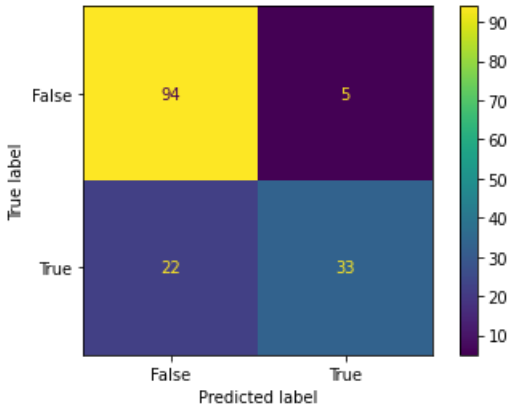
In [ ]:
```
accuracy_svm = accuracy_score(y_test, y_pred_svm)
precision_svm = precision_score(y_test, y_pred_svm)
recall_svm = recall_score(y_test, y_pred_svm)
f1_svm = f1_score(y_test, y_pred_svm)
```

In [ ]:
```
cr_svm = classification_report(y_test, y_pred_svm, output_dict=True, zero_division='warn')
pd.DataFrame(cr_svm)
```

Out[ ]:

| | 0.0 | 1.0 | accuracy | macro avg | weighted avg |
|---|---|---|---|---|---|
| **precision** | 0.810345 | 0.868421 | 0.824675 | 0.839383 | 0.831086 |
| **recall** | 0.949495 | 0.600000 | 0.824675 | 0.774747 | 0.824675 |
| **f1-score** | 0.874419 | 0.709677 | 0.824675 | 0.792048 | 0.815582 |
| **support** | 99.000000 | 55.000000 | 0.824675 | 154.000000 | 154.000000 |

In [ ]:
```
cm_display_svm = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_test, y_pred_svm), display_labels=
cm_display_svm.plot()
plt.show()
```




## Comparing Classification Scores

In [ ]:
```
comparison_data = (('Naive Bayes', accuracy_gnb, precision_gnb, recall_gnb, f1_gnb),
                   ('K Nearest Neighbor', accuracy_knn, precision_knn, recall_knn, f1_knn),
                   ('Support Vector', accuracy_svm, precision_svm, recall_svm, f1_svm))
```

In [ ]:
```
pd.DataFrame(comparison_data, columns = ('Comparison algorithm','Accuracy','Precision','Recall','F-measure'))
```

Out[ ]:

| | Comparison algorithm | Accuracy | Precision | Recall | F-measure |
|---|---|---|---|---|---|
| **0** | Naive Bayes | 0.759740 | 0.680000 | 0.618182 | 0.647619 |
| **1** | K Nearest Neighbor | 0.831169 | 0.837209 | 0.654545 | 0.734694 |
| **2** | Support Vector | 0.824675 | 0.868421 | 0.600000 | 0.709677 |